Monte Carlo Simulation of Streamflow of the Salt River, Arizona

Marina Timofeyeva and Rachael Craig

Abstract: Evaluations of the impact of climate change (such as a greenhouse effect) upon water resources should represent both the expected change and the uncertainty in that expectation. Since water resources such as streamflow and reservoir levels depend on a variety of factors, each of which is subject to significant uncertainty, it is desirable to formulate methods of representing that uncertainty in the forcing factors and from this determine the uncertainty in the response variables of interest. We report here progress in the representation of the uncertainty in climate upon the uncertainty in the estimated hydrologic response. These uncertainties are represented in Monte Carlo simulations of local climate and hydrology. For illustration we show solutions for a 5 km x 5 km grid over an area of about 30,000 km^2 that contains the drainage of the Salt River, Arizona. This river forms a critical water supply for the greater Phoenix area and the utility of the water supply is dependent upon wintertime snowfall and timing of snowmelt.

Results of the Local Climate Model are monthly mean maximum daily temperature (TMAX) and total monthly precipitation (PREC). We also derive standard deviations for TMAX and log(PREC) as the standard error of the regression of the canonical correlation model. Together they form the spatially-varying parameters of frequency distributions of TMAX (normal) and PREC (lognormal) at each point of a grid. Monte Carlo perturbation of climate using these parameters provides stochastic input into a mainly deterministic (mass balance) hydrology model. Results of the hydrology model with this stochastic input are long-term monthly runoff over each grid cell, and discharge at selected sites which can be compared to observed discharges at the same point.

Comparison of 78 years of modeled and observed streamflow at Roosevelt Lake shows that modeled mean discharges are very close to the observed values; but, the modeled standard deviation of discharge can differ from observed by a factor of two or three. Analysis of standard deviation of precipitation at 14 stations within the solution domain has shown long-term variations from one 10-year period to another of 2x to 5x, which may explain these discrepancies. Another explanation of the discrepancies in the standard deviation of discharges may arise from use of boundary conditions for average conditions rather than the same time period being tested.

Introduction

Water resources may be one of the most vulnerable components of the earth system when considering future climate change associated with a greenhouse effect (Lins *et al* 1991). The sensitivity of the hydrologic system to climatic change makes our society vulnerable to impacts on various critical facilities such as reservoirs, hydroelectric plants, and irrigation and flood control structures. There is considerable debate whether the uncertainties in existing models of climate change allow clear statements of expected hydrologic impacts. We report here a method to represent the uncertainty in computed hydrology given the uncertainty in the controlling climate.

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Various approaches are available to estimate the characteristics of a regional hydrologic system that can be expected in a different climate (Arnell 1992; Bultot *et al* 1992; Gleick 1987; Kite *et al* 1994; Panagoulia 1992; Cole *et al* 1991; McCabe and Ayers 1989). Typical of the current state of methods is the work of Kwadijk and Middelkoop (1994), who use monthly temperature and precipitation solved from a coarse resolution GCM to compute discharge of the Rhine River for a 2xCO_2 scenario. Examination of the uncertainties in such estimates of discharge typically is achieved through sensitivity analysis (Lettenmaier and Gan 1990).

Richardson (1981) shows a method of stochastic simulation of climate variables, and Ming-Ko Woo (1992) extends this idea by using stochastic simulation to represent climate and climate variability under a 2xCO_2 scenario. We know of no examples where a stochastic model of climate has been used to compute both the expected value and variance of streamflow under a climate change scenario. Our purpose here is to illustrate a method to achieve this, and we illustrate this method with an example from the Salt River, Arizona, which is a critical water supply for Phoenix and which derives much of its flow from snowmelt.

Our method makes use of a stochastic model of climate called the Local Climate Model (CGM). An earlier version of the LCM has been described by Craig and Stamm (1990), and results of validation of that model were reported by Stamm and Craig (1992). Orndorff, Craig, and Stamm (1993) linked the climate model to a calculation of hydrologic mass balance in a model with one soil layer, and Orndorff and Craig (1994) illustrated application of a two-layer version of that model (Orndorff 1994) in the Truckee River drainage. In this study we use a more recent version of the LCM described by Stamm and Gettelman (1995) to calculate climate.

The LCM computes mean monthly maximum daily temperature (TMAX) and total monthly precipitation (PREC) using a canonical-regression function (Stamm and Gettelman 1995). Solution of the canonical-regression function requires computation of a set of predictor variables which represent the influence of five boundary conditions: terrain, sea surface temperature, wind fields, atmospheric CO_2 concentration, and solar radiation. The values of these boundary conditions define the climate scenario solved by the model.

The snow and surface hydrology model (SSHM) used in this study is mostly deterministic and based on linkage of separate models reported by Orndorff (1994). SSHM uses climate as the forcing factor in the monthly runoff and streamflow discharge computation. Runoff is computed for each grid cell of the solution domain, and discharge is computed for specific locations of the watershed.

Method

The climate model used was described by Stamm and Gettelman (1995). We have used that model to compute TMAX (°C) and PREC (mm) for drainage basins of the Salt River and Verde River in Arizona at a horizontal grid resolution of 5 km by 5 km (Figure 1). These values (Figure 2a,b) represent the expected value of a canonical regression model at each grid cell based on the values of 22 independent variables calculated at that grid cell by the climate model based on the General Circulation Model calculated history of air masses reaching that cell in January and July. These expected values are supplemented by estimates of the standard deviation of TMAX and of PREC at each grid cell (Figure 2c,d) by calculation of the *standard error of the regression* (Draper and Smith 1981) using the same independent variables at that cell.

We have linked together the LCM, with the hydrology and snow models modified from those reported by Orndorff (1994). Our modification of Orndorff's models joins the snow and hydrology models into one and adds a Monte Carlo element to perturb the input climate parameters so that the long-term statistical variability of climate becomes the input to a sequence of simulated years of runoff and streamflow. Variance of TMAX and PREC is computed as the standard error of the regression for the regression equations from which climate is solved. We assume TMAX is normally and independently distributed and that PREC is log-normally and independently distributed. Successive draws from these distributions represent the seasonal cycle of climate at a monthly time step through a sequence of years. From that input we calculate the hydrologic properties of a grid of points within a drainage basin. For our example, we use 78 years of simulated record, which matches the length of discharge record of the Salt River available at Roosevelt Lake, Arizona, where we computed discharge. Computed runoff is totaled for all grid points in a drainage basin to yield an estimate of streamflow, and the variability of the predicted streamflow through the sequence of simulated years gives a measure of the uncertainty in the hydrologic response as a function of the uncertainty in climate.

Runoff is calculated for each grid cell using a parameterized mass-balance approach. PREC is partitioned into snow and rain according to TMAX and assumed values for the environmental lapse rate and the fall velocity of snow. Snowpack can accumulate through the season, and snowmelt is calculated using an index method dependent upon TMAX. Infiltration may be stored in a surface (soil) layer and from there may be used to satisfy evapotranspiration needs (calculated with the Blaney-Criddle equation and a depletion term) or may recharge a groundwater layer from which baseflow is extracted at a fixed rate limited by a depletion term. Parameter values are the same as those derived by Orndorff (1994). Calculations are iterative through each simulated year

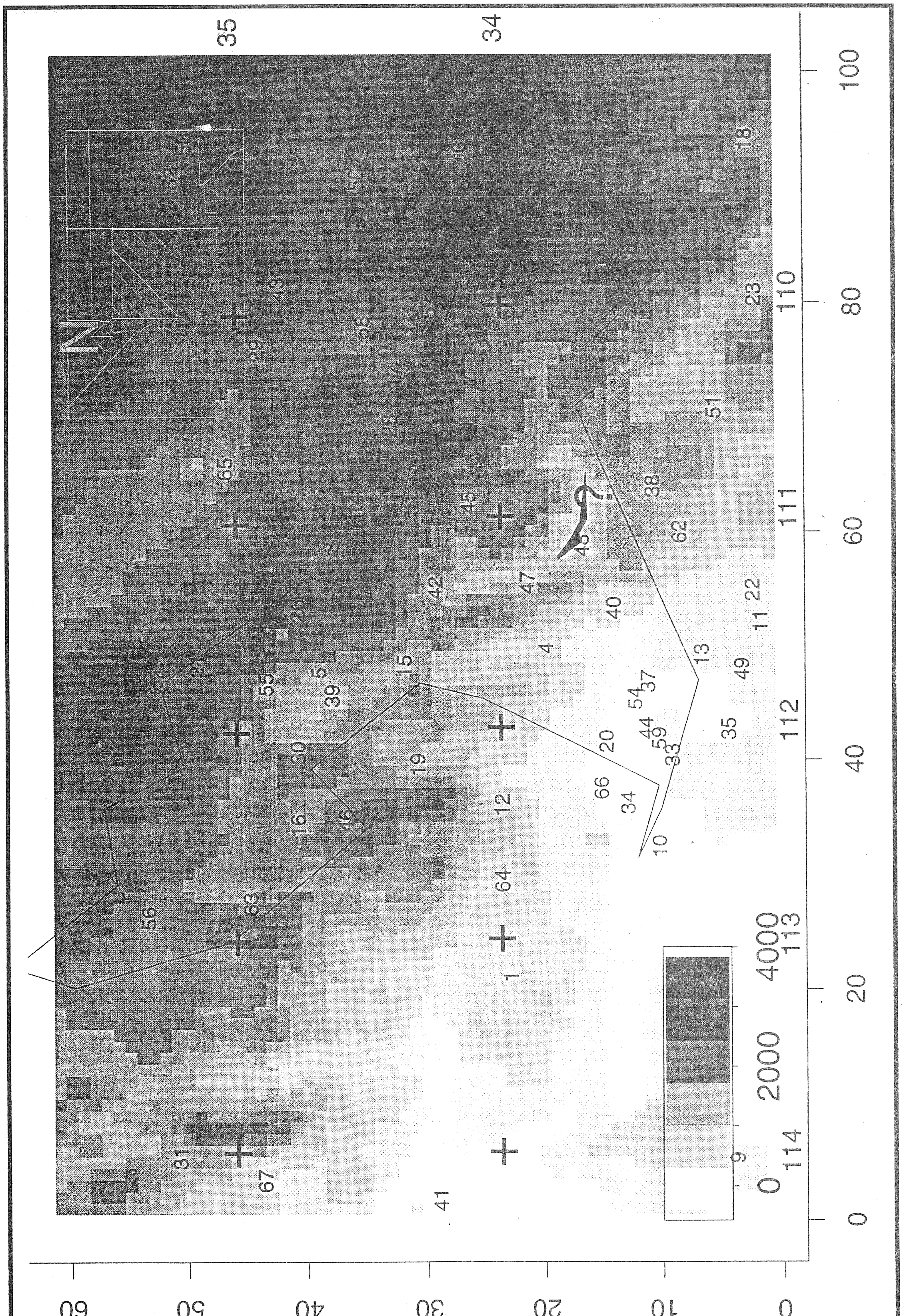

Figure 1 Solution domain for calculation of climate and hydrology.

Shades represent elevation (m) as shown in the accompanying legend. The drainage basin outline of the Salt and Verde rivers is shown schematically. Grid cell numbers are shown on the outer axis, and each cell is 15 km square. Dark tick marks within the figure mark latitude-longitude intersections, which are labeled at the inner margins. Numbers within the figure show locations of climate stations referred to in the text. The Roosevelt Lake gaging station is shown by a "?" Index map gives the setting of the grid within Arizona.

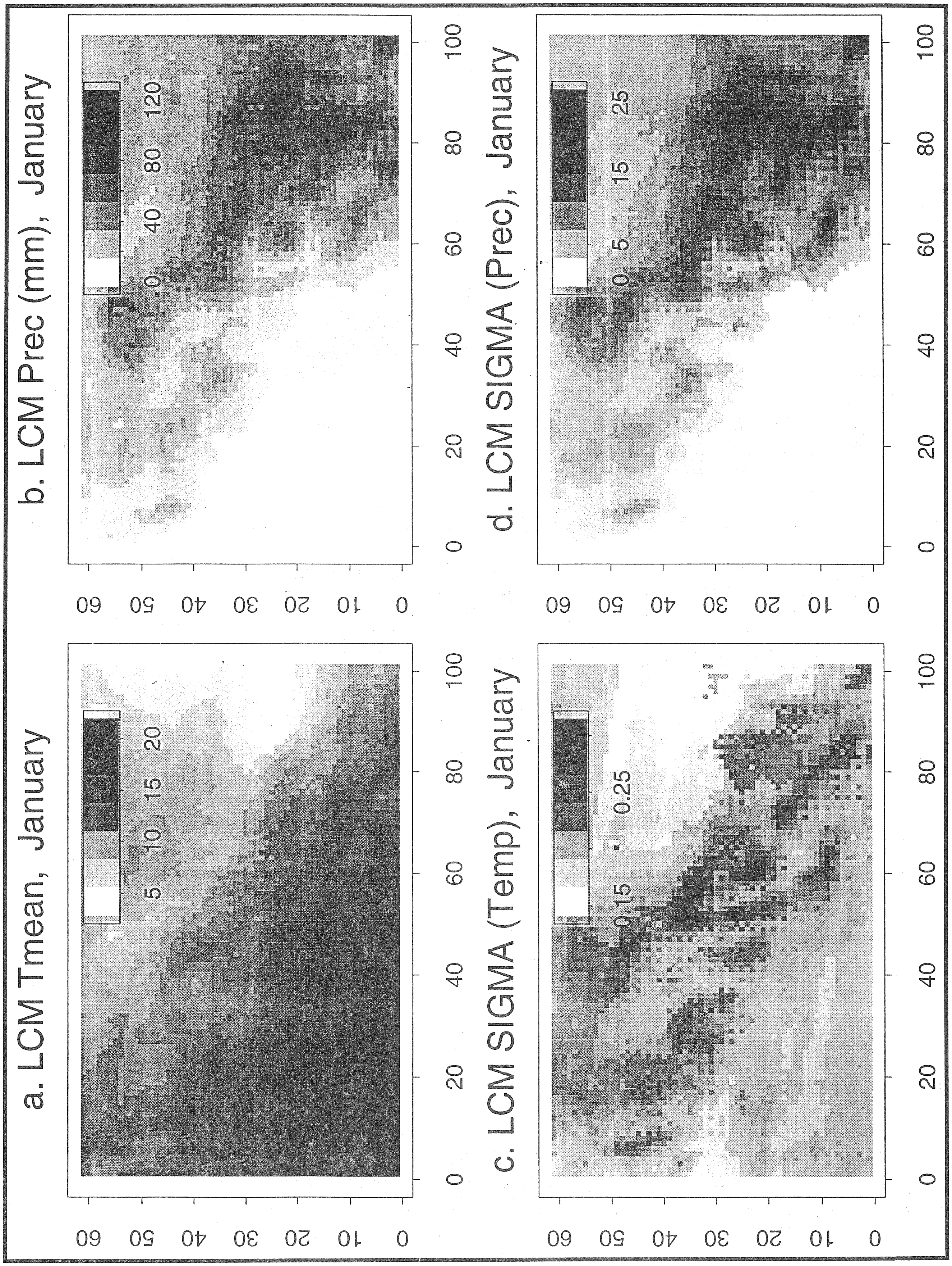

Figure 2 Example solutions of climate (for the same area as in Figure 1) for January.

until the soil moisture equilibrates. We use the method of Singer (1985) to calculate those grid cells draining to the grid cell representing the Salt River gaging station at Roosevelt Lake. Runoff for all grid cells draining to the Salt River at Roosevelt Lake (Figure 3, top) is summed to estimate discharge.

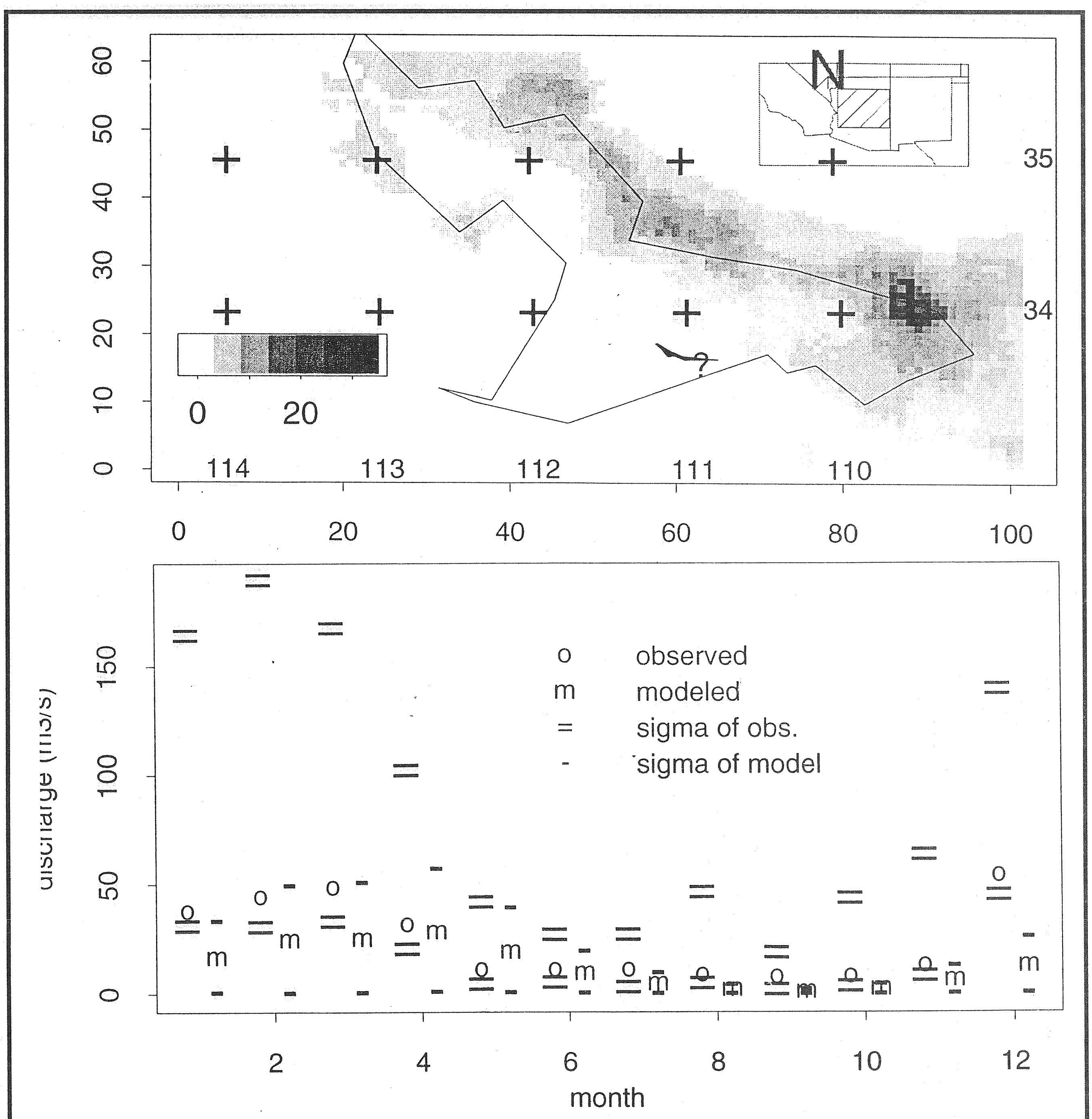

Figure 3 (Top) Calculated annual runoff (cm) for the same area as shown in Figure 1.
(Bottom) graphical representation of discharge statistics at Roosevelt Lake for 78 years simulated and observed.

Numbers represent mean discharge for the corresponding month and the ticks above and below the corresponding number represents the mean plus or minus one standard deviation.

Results

Before evaluating the hydrologic simulation, we first examine results of the climate model and of the Monte Carlo simulations based on the expected climate. Our examination of the calculated climate is made by comparing model solutions to observed instrumental records of climate at 67 stations in the solution domain for 1975-1979. Here we report comparisons for January and July. Figure 4a compares the expected value of temperature estimated by the model to that observed. There is a close correspondence between observed and predicted, although there is a constant bias of about 1-2°C, with the model tending to estimate temperatures that are too cool. This may be because the climate model was calibrated primarily with instrumental records from more northerly locations in the western United States, which may have biased the model to cooler temperatures. The means calculated from a Monte Carlo simulation of 5 years of January temperature (Figure 4b) based on these expected values and the standard error of the prediction show the same bias and, in general, reproduces the average statistics very well.

The model estimate of July temperature provides an even closer match to observed (Figure 4c) and (unlike January) with no constant bias. The closer match may be due to the smaller north-to-south temperature gradient in the western United States during summer. In Figure 4c we do see a small linear bias in which the model is too warm at the low temperatures (high-elevation sites) and too cool at high temperature (low-elevation) sites. We assume this bias arises because the model estimates are calculated for the average elevation of the 5 km by 5 km grid cell rather than for the exact elevation of the climate station. Because of this, the model computes a temperature for an elevation higher (lower) than the climate station and therefore cooler (warmer).

Model estimates of mean precipitation are less satisfactory (Figure 4d). In this case there is the same constant bias in estimates of January PREC as was seen for January TMAX; but, the model tends to estimate a wetter climate than observed — consistent with the cooler temperatures and probably due to the same calibration bias. Except for a few stations, the correspondence is within a factor of two (Figure 4e). Considering that observed January precipitation can vary by a factor of two, or even five, from one 5-year period to another (Figure 5) this discrepancy may be attributable to actual variability. The fact that the model tends to overestimate PREC could be because the model was calibrated for a relatively wet period in the record (hachured box in Figure 5). For the Monte Carlo estimates of PREC, the model calculates the expected value and standard error of the prediction of the natural log of PREC. We exponentiate each estimate and report the mean of these values. The Monte Carlo estimates of January PREC (Figure 4e) again suggest that the model tends to slightly overestimate PREC, this time with a slight systematic bias. The

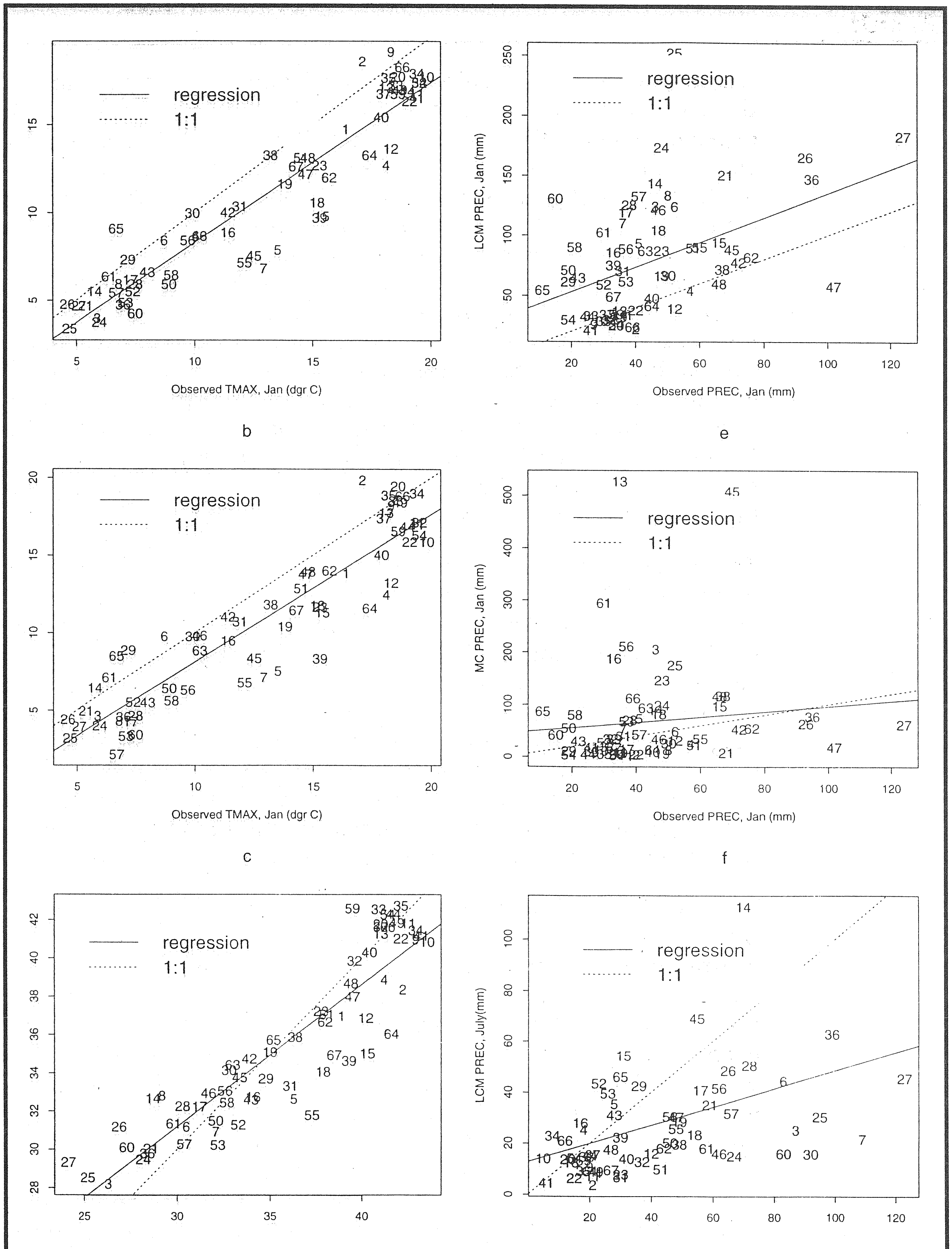

Figure 4. Comparison of observed mean TMAX and total PREC with:
(a) modeled mean TMAX for January, (b) mean of Monte Carlo estimates of TMAX for January, © modeled mean TMAX for July,
(d) modeled total PREC for January, (e) mean of Monte Carlo estimates of PREC for January, (f) modeled PREC for July.

Numbers on each plot correspond to stations shown in Figure 1. Also shown are the 1:1 line (dashed) and a line based on a simple linear regression with "observed" as the independent variable.

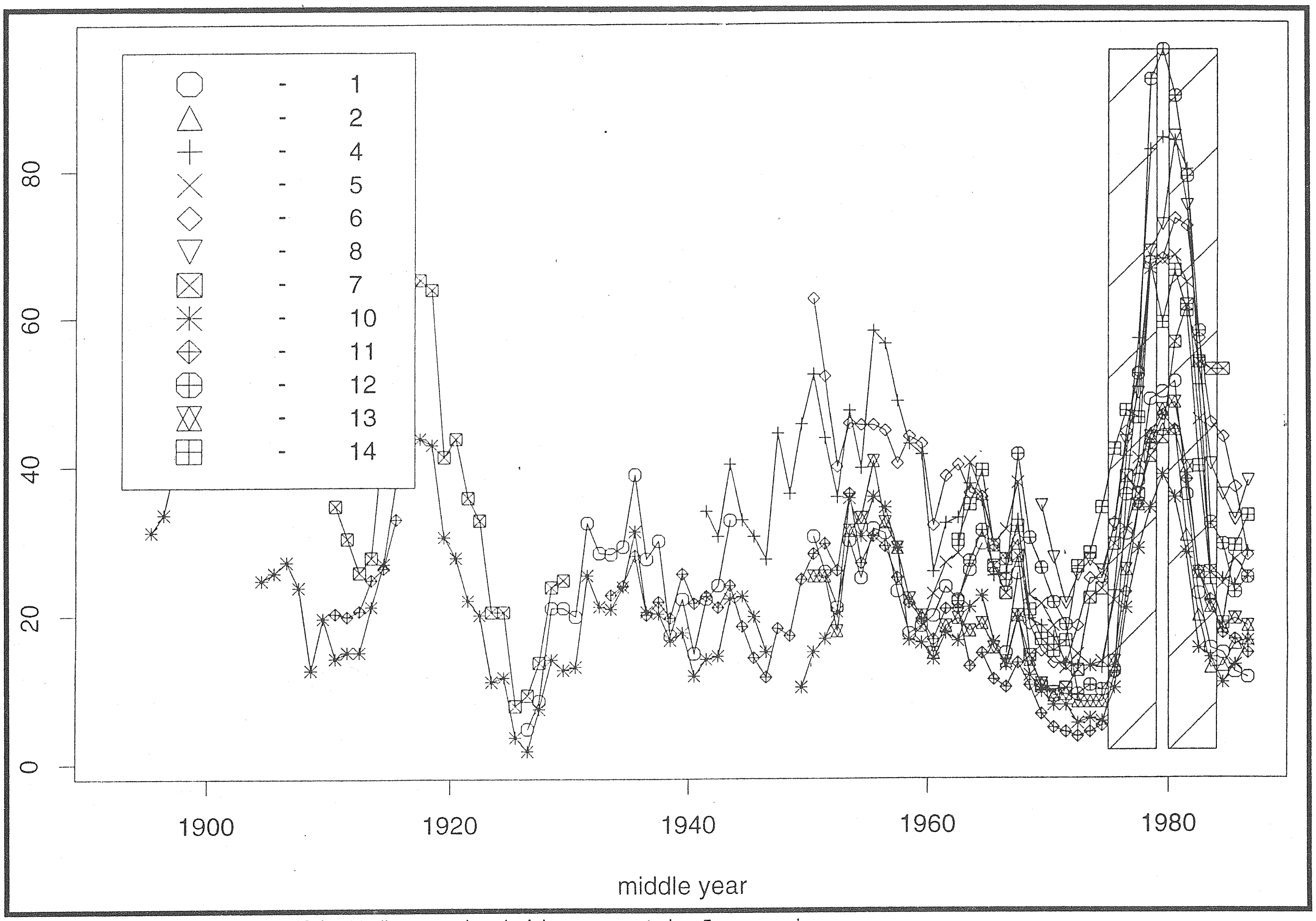

Figure 5. Temporal patterns of PREC for 12 climate stations in Arizona computed as 5-year running averages.

The hachured boxes enclose the periods 1975-1979 and 1980-1984 used for calibration of the LCM. Station numbers correspond to those in Figure 1. Five-year averages are plotted at the location of the middle year.

greatest errors occur at stations 13, 45, and 61, which are at low, intermediate, and high elevations, respectively. Thus, no systematic bias with elevation is apparent. In general, the stations with very low calculated PREC are those at the lowest elevation sites, so the simulation seems to capture the orographic effect well. For July, the pattern is similar to that for July TMAX estimates (Figure 4f); there is a tendency for a linear bias with a slope less than one leading to estimates of PREC that are slightly too high in dry areas and too low in wetter (high elevation) areas, suggesting that the grid cell elevations for which solutions are made are not as high (or low) as the actual climate station elevations, which is consistent with the bias seen in Figure 4c.

Calculated annual runoff (Figure 3 top) shows the strong spatial pattern expected in an area dominated by orographic precipitation (compare to Figure 1). Most of the runoff in this area is generated by winter rainfall and spring snowmelt, with a minor contribution from summer monsoons. The model predicts that most runoff is generated along the topographic transition between the desert of the southwest and the high plateau of the northeast, and this corresponds to the actual case.

Discussion

A comparison between observed and calculated discharge for the gaging station at Roosevelt Lake is shown in Figure 3 (bottom). A bias toward too low estimates of discharge in winter (months 12, 1, 2, 3) and toward too high estimates of discharge in the melt season (months 4, 5, 6) can be seen. Observed annual discharge averaged (unweighted) across months is 25.5 cms, whereas the modeled average discharge is 18.8 cms. Considering the coarseness of the climate solution and the simplicity of the hydrologic model, the correspondence (*ie,* mass balance) is quite remarkable.

Figure 3 (bottom) also provides a visual representation of the variability of observed and modeled discharge. The ticks surrounding each month's average value correspond to the values of mean ± one standard deviation calculated with the lognormal model (Aitchison and Brown 1957, equation 2.7). The variability modeled for April, May, and June (high snowmelt months) corresponds nearly perfectly to that observed. Winter months have greater variability than modeled, and the warmer (and drier) months have less variability than is modeled. In general the variability is captured within a factor of two, as was true for precipitation. It is interesting that calculation of mean discharge at this site using the output of the LCM directly and so without Monte Carlo perturbations and inclusion of the standard deviation relationship of Aitchison and Brown (1957) gives a mean discharge of 17, which is at greater deviance from observed than the value obtained by the simulation technique, as would be expected according to theory. This supports the concept that proper estimates of the mean discharge require knowledge of both mean and variance of the climate parameters.

Why is the estimated discharge too high in winter and too low in the snowmelt months? This could be explained by the constant bias toward too low temperatures in winter, as suggested in Figure 4a, which would tend to lead to a greater fraction of precipitation estimated to fall as snow in winter. This snow would be stored as snowpack in the winter, leading to lower discharge in winter and overestimation of discharge when it melts in spring. The estimate of winter snow fraction is based on a relationship to mean monthly temperature. Orndorff (1994) estimated mean monthly temperature by subtracting a constant (12°C) from TMAX, and that constant was determined by calibration using records from 52 stations in California and Nevada. However, the data of Orndorff (1994, Figure 4.4) show that the "constant" is never greater than 11°C and may be as low as 9°C in winter, with a mean of 10.5°C. If we modify the correction parameter of Orndorff (1994) to correspond to the observed values that he reports in his Figure 4.4, there is a slight decrease in modeled streamflow in winter but a great decrease in spring, so that the modeled discharge in spring closely matches observed and overall the fit is improved.

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References

Aitchison, J., and J.A.C. Brown. 1957. *The Lognormal Distribution*. Cambridge Univ. Press, 176 p.

Arnell, N.W. 1992. Factors controlling the effects of climate change on river flow regimes in a humid temperate environment. *Journal of Hydrology*, 132:321-342.

Bultot, F., D. Grllens, M. Spreafico, and B. Schadler. 1992. Repercussions of a CO2 doubling on the water balance — a case study in Switzerland. *Journal of Hydrology*, 137:199-208.

Cole, J.A., S. Slade, P.D. Jones, and J.M. Gregory. 1991. Reliable yield of reservoirs and possible effects of climate change. *Hydrological Sciences Journal*, 36:579-598.

Craig, R.G., and J.F. Stamm. 1990. A statistical model of climates in the southwestern U.S. Pages 27-31 in *Proceedings of the Sixth Annual Pacific Climate (PACLIM) Workshop*. J.L. Betancourt and A.M. Mackay, eds., Calif. Dept. Water Resources, Inter. Ecol. Stud. Prog. Tech. Rept. 23.

Draper, N., and H. Smith. 1981. *Applied Regression Analysis, 2nd Ed.* John Wiley, NY, 709 pp.

Gleick, P.H. 1987. Regional hydrologic consequences of increases in atmospheric CO2 and other trace gases. *Climatic Change*, 10:137-161.

Kite, G.W., A. Dalton, and K. Dion. 1994. Simulation of streamflow in a macroscale watershed using general circulation model data. *Water Resources Research*, 30:1547-1559.

Kwadijk, J., and H. Middelkoop. 1994. Estimation of impact of climate change on the peak discharge probability of river Rhine. *Climatic Change*, 27:199-224.

Lettenmaier, D.P., and T.Y. Gan. 1990. Hydrologic sensitivities of the Sacramento-San Joaquin river basin, California, to global warming. *Water Resources Research*, 26:69-86.

Lins, H.F., I.A. Shiklomanov, and E.Z. Stakhiv. 1991. Impacts on Hydrology and Water Resources. Pages 87-97 in *Climate Change: Science, Impacts and Policy*. J. Jager and H.L. Ferguson eds. Proceedings of the Second World Climate Conference, Cambridge University Press.

McCabe, G., and M.A. Ayers. 1989. Hydrologic effects of climate change in the Delaware River basin. *Water Resources Bulletin*, 25:1231-1241.

Ming-Ko Woo. 1992. Application of stochastic simulation to climatic-change studies. *Climatic Change*, 20:313-330.

Orndorff, R.L. 1994. Development of a Surface Hydrologic Model and its Application to Modern and Last Glacial Conditions. Unpublished Ph.D. Dissertation, Kent State University, Kent, OH, p. 178.

Orndorff, R.L., and R.G. Craig. 1994. Modeling the effect of snow on seasonal runoff within the Truckee River Drainage Basin. Pages 107-116 in *Proceedings of the Tenth Annual Pacific Climate (PACLIM) Workshop*. K.T. Redmond and V.L. Tharp, eds. California Department of Water Resources, Interagency Ecological Studies Program, Technical Report 36.

Orndorff, R.L., R.G. Craig, and J.F. Stamm. 1993. A stochastic model of temporal variations in monthly temperature, precipitation, snowfall, and resulting snowpack. Pages 165-172 in *Proceedings of the Ninth Annual Pacific Climate (PACLIM) Workshop*. K.T. Redmond, *ed.*, California Department of Water Resources, Interagency Ecological Studies Program, Technical Report 34.

Panagoulia, D. 1992. Impacts of GISS-modelled climate changes on catchment hydrology. *Hydrological Sciences Journal*, 37:141-163.

Richardson, C.W. 1981. Stochastic simulation of daily precipitation, temperature, and global radiation. *Water Resources Research*, 29:2335-2344.

Singer, M.P. 1985. A Computer Simulation Model of the Growth and Desiccation of Pluvial Lakes in the Western Great Basin, U.S. Unpublished M.S. thesis, Kent State University, p. 436.

Stamm, J.F., and R.G. Craig. 1992. Validation of a semi-Lagrangian, canonical regression model of climates in the southwestern United States. Pages 163-171 in *Proceedings of the Eigth Annual Pacific Climate (PACLIM) Workshop*, K.T. Redmond, ed. California Department of Water Resources, Interagency Ecological Studies Program, Technical Report 31.

Stamm, J.F., and A. Gettelman. 1995. Simulation of the effect of doubled atmospheric CO2 on the climate of Northern and Central California. *Climatic Change*, 30:295-325.